

# THE EFFECTIVENESS OF E-TAILERS' COMMUNICATION PRACTICES IN STIMULATING SALES OF SLOW-SELLING VERSUS BEST-SELLING PRODUCTS

*Completed Research Paper*

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## Abstract

*Based on 60,000 books (approx. 2m purchase decisions) from Amazon.de, we analyze the interplay of four e-tailers' communication practices – presenting product networks (recommendation systems), social features (eWOM, i.e. user-generated content), free trial, and vivid content – and demonstrate how they vary in effectiveness for influencing consumers' purchase decisions online. Additionally, little is known about effects of these practices on driving sales across the sales distribution from bestsellers to niche products. Long tail theory predicts that consumers will become particularly attracted to buying niche products as those match personal preferences better than mainstream products. However, our large-sample results are partly counter to the theoretical predictions and previous studies in the field (as both bestsellers and niche products gain sales at the expense of medium popular products). We offer a clearer understanding of the varying functionality of online communication practices that helps retail managers select, combine and focus their communication practices.*

**Keywords:** Business strategy, Business benefits, Communication

## Introduction

The Internet has profoundly transformed the way consumers shop and the way they gather and exchange information on consumption experiences (Pan and Zhang 2011). However, the “intangible”, experiential nature of e-commerce causes shoppers to be uncertain if goods offered online will fit their needs and perform up to expectations (Weathers et al. 2007). To reduce purchase uncertainties, consumers engage in *search* for information relevant to the purchase decision. Depending on the amount and quality of information available, search processes can turn out time-consuming and complex, thereby incurring considerable costs for consumers.

Retailers can significantly decrease online shoppers' search costs by implementing specific communication tools that provide consumers with relevant information. ‘Long tail’ theory, introduced by Anderson (2006) – describing the e-retailing strategy of selling a large number of individual items with relatively small quantities sold of each, mostly, in addition to selling a limited number of popular items in large quantities – assumes that reducing consumers' search costs is particularly effective for increasing demand for “niche” products (Anderson 2006): Niche products' sales will profit disproportionately

strongly from search cost reductions, as consumers are now able to locate products that match their preferences better than do mainstream products (Brynjolfsson et al. 2011). Accordingly, long tail theory scholars widely believe that expanding product assortments while decreasing search costs for consumers leads to an increasing heterogeneity in consumption patterns (e.g. Brynjolfsson et al. 2011). In line with long tail theory, we expect that presenting product networks (recommendation systems), social features (eWOM, i.e. user-generated content), free trial, and vivid content should allow consumers to seek out greater variety. Consequently, a decline in consumer search costs is expected to work towards evening out sales between popular and niche products, leading to a “flattening” of the sales distribution curve (Brynjolfsson et al. 2003; Brynjolfsson et al. 2011).

Against this background, e-retailers are faced with two essential decisions: (1) what products to carry or feature, i.e. whether to focus on bestsellers vs. lower selling goods, and (2) how to design communication practices that best promote these offerings (Weathers et al. 2007). A clear understanding of how online communication strategies impact consumer product evaluations and choices could help retail managers, including those who manage both electronic and brick-and-mortar channels, enhance product display and increase consumer confidence (Weathers et al. 2007). However, empirical evidence on the relative effectiveness of different communication practices for influencing consumer choices, and on their impact on sales prospects in the various parts of the sales distribution from bestsellers to low-selling goods, is sparse. In this paper, we explore these questions.

Based on innovative methodology and data for initially 60,000 books (approx. 2 million purchase decisions) at Amazon.de, we demonstrate that four distinct communication practices increasingly used by e-retailers – presenting product networks (recommendation systems), social features (eWOM, i.e. diverse kinds of user-generated content), free trial, and vivid content – largely vary in their effectiveness for influencing consumers’ purchase decisions when shopping experience goods online, overall as well as in the various parts of the sales distribution. The results also indicate that increasing the use of some communication practices could drive consumers to purchase especially niche offerings (Anderson 2006). Yet, sales gains by niche products could concur with a shift of the sales curve that differs from the predictions made by long tail theory and the few previous studies in the field.

Our contributions are: As regards practical implications, retailers often fear that reducing search costs leads to intensified consumer search and in consequence, to increased competition. Yet, our results provide insights into integrating assortment and promotional strategies in a way that takes advantage of changes in consumer search behavior, help retailers select, combine and focus communication practices, and show how to adapt such practices to the various parts of the sales distribution.

As regards theoretical contributions, we study the relative impact of four increasingly applied communication practices, which have not been studied together in previous research. Moreover, so far, little is known about effects of search cost reduction on sales prospects across the sales distribution. We also integrate demand drivers that have been largely overlooked (e.g. forums, free trial, supply shortage). Interestingly, our results also indicate a shift in the sales curve in response to search cost reductions that is different from the predictions of long tail theory.

As regards methodological contributions, studies often measure product choices based on consumer intentions or stated preferences, but they cannot detect actual and stated behavior differences. We focus on economic measures (sales and sales ranks; see also, Chevalier and Goolsbee 2003a; Chevalier and Mayzlin 2006). Additionally, using unconditional quantile regressions (UQR) instead of traditional quantile regression (QR) reveals the impact of the explanatory variables on the unconditional (marginal) distribution of sales, and permits more robust conclusions on the variables’ effects (Firpo et al. 2009). Based on 60,000 books (and around 2million buying decisions for these books) from Germany’s biggest book retailer Amazon, we also provide the first long tail sales-ranks “conversion model” for a sizeable market *outside* the U.S.

The next section presents the conceptual framework. Subsequently, we develop hypotheses. Next, we present the data. Then, we describe methods and model specifications, afterwards, we reports the results. The last section concludes, offering managerial and research implications

## Conceptual Framework

### ***Effects of Communication Practices on Consumer Choices of Experience Goods***

The literature interprets consumers' search for adequate goods as a two-stage process – first, the discovery of products; second, an assessment of fit between the product's characteristics and the consumer's quality and functional requirements. Presently, outcomes of such search processes are increasingly affected by changes in technology and consumer behavior (Chen et al. 2004). Although consumer information processing and search outcomes have been a focus of marketing and consumer behavior research, potential effects of online information provision by retailers via the increasing use of online communication practices yet have to be established.

Consumers search for and process information in a goal-oriented fashion. Analyses of the economics of search behavior imply a cost-benefit framework: Consumers search more if the search costs are low and/or if the benefits of additional search are high (Senecal and Nantel 2004). E-retailers can reduce consumers' search costs, resulting from their attempts to identify and evaluate products, by supporting search processes through various communication practices. One option is to implement product networks, where each product is connected by links to other webpages that feature complementary products (e.g. Anderson 2006; Goldenberg et al. 2011; Oestreicher-Singer and Sundararajan 2012). Following product recommendation links, customers can locate similar products that match their preferences more easily, thus incurring lower search costs compared with unaided or even random search attempts. Senecal and Nantel (2004) show experimentally that online recommendations influence consumer choice, and that electronic recommendations can even be more influential than human ones.

Apart from product networks that help consumers locate products, *social features* offered by online retailers can especially help reduce quality uncertainty. Lately, online retailers have begun to combine their product linkings with social features, like online communities and forums, that enable consumers to share their opinions and consumption experiences (Goldenberg et al. 2011). Accordingly, recent empirical evidence draws particular attention to the significance of social exchange for driving demand in online markets (e.g. Brynjolfsson et al. 2011; Elberse and Oberholzer-Gee 2006; Oestreicher-Singer and Sundararajan 2012; Zhu and Zhang 2010). On the one hand, social influence could increase the importance of fads and blockbusters; however, if people use social exchange to self-segregate into smaller groups, or to learn about and develop idiosyncratic tastes, the effect of online social features will be increased balkanization and a favoring of niche products (Brynjolfsson et al. 2010). Research on information transmission capabilities of communication tools has further placed a focus on *vividness*, meaning the extent to which sensory information is provided. Online retailers can offer vividness through the presence of product pictures, which can compensate for a lack of haptic information and increase confidence in product evaluations. Besides, consumer uncertainty when buying experience goods can also be decreased by offering a free trial that helps assess product quality (Weathers et al. 2007).

### ***Effects of Communication Practices in the Sales Distribution: Aggregate Perspective***

The world of retailing has traditionally been believed to follow the Pareto principle, where 80 percent of sales are generated by only 20 percent of the offered products (Brynjolfsson et al. 2011). Consequently, producing and marketing hit products has long been the focus of attention. So far, little is known about the effects of search cost reductions on sales prospects across the sales distribution. According to long tail theory, in response to search cost reductions, consumers will be attracted particularly to buying niche products as those are expected to match personal preferences better than mainstream products (Anderson 2006). The notion is based on the assumption that search costs are heterogeneous across products: Hits are "cheap" to find as they are heavily promoted by marketing campaigns, whereas locating niche products requires investing high search costs because they are not as visible (Brynjolfsson et al. 2011). That is, expanding product assortments while decreasing search costs for consumers leads to an increasing heterogeneity in consumption patterns (Brynjolfsson et al. 2011, 2010). Hence, long tail theory predicts a change in the sales distribution, as sales are supposed to gradually even out across the entire offering (Anderson 2006). In fact, Brynjolfsson et al. (2011) find that the sales concentration in clothes retail is lower online than in conventional channels. Elberse and Oberholzer-Gee (2006) report

decreasing online sales concentration for video titles, concluding that e-distribution is triggering changes in consumption patterns, but that the drivers of such changes are not yet understood.

Given that e-retailers can decrease consumers' search costs through implementing communication practices, these practices should directly affect sales. Although it is possible that recommendation systems could be tuned so that they lead to sales gains particularly, for *popular* products, Oestreicher-Singer and Sundararajan (2012) find evidence that recommendations reduce sales concentration as sales migrate from the hits to the niche. Chen et al. (2004) show that Amazon's recommendations improve sales more for less popular than for more popular books. Similarly, with respect to social influence, user-generated online content may especially influence sales for niche products, since user-generated information may often be the only source of information available (Chevalier and Mayzlin 2006). Tucker and Zhang (2011) show that information on the offering's popularity with other consumers benefits niche choices disproportionately, as for consumers high popularity of niche offerings is associated with higher quality compared with broad-appeal offerings. Then, greater diversity in consumption patterns induced by adequate communication practices should result in a "flattening" of the sales curve.

Brown and Dant (2009) noted that researchers who investigate topics involving the internet should utilize theories not frequently applied, like microeconomic theory, consumer choice or social exchange theory. Our analysis is based on long tail theory, and on the microeconomic standard model of expected utility maximization which implies that consumers choose an object over another if this object is assigned a higher value by their individual preference function (Hirshleifer 1965). We assume that consumers try to achieve the highest level of utility possible in choosing a particular good. Yet obviously, they face constraints in satisfying their wishes as extended search for the "most adequate" good becomes complicated and time-consuming. Consumers' rationality in forming preferences is limited by the information they can acquire, by cognitive limitations, and by the finite amount of time available to reach a decision. Consequently, purchase decisions will be based on a certain range of decision drivers. We study communication practices as such potentially effective drivers of consumer choice, using the context of online book retailing. To develop the argument, we integrate arguments from marketing, retailing and economics with long tail theory. This interdisciplinary set-up is further motivated by Dant's (2008, p. 93) argument for worth-while diversity in research perspectives, as he notes, "Authors are beginning to examine research questions from a phenomenological perspective rather than within the confines of single theoretical frameworks." The next section presents hypotheses.

## Hypotheses

Consumers can use recommendation systems to locate goods that match their preferences. For each book, Amazon.de offers an initial list of up to six recommendations for books on related topics, based on other customers' co-purchase decisions ("Customers Who Bought This Item Also Bought"). Thereby, recommendations increase the amount of customer traffic which goes to a particular product's page. In consequence, goods that receive such automatically generated recommendations may sell better due to their higher visibility. Recommendations also provide additional information on content and quality for all the co-purchased books, because they inform consumers what buying alternatives other consumers perceive as serving similar needs, and they allow consumers connecting unknown goods to possibly more familiar ones.

*Hypothesis 1. A prominent position in the product network positively influences the good's sales.*

User-generated content in terms of online product reviews can increase customer awareness for the discussed offerings. Besides, eWOM is sometimes the only source of detailed information available, making it essential for assessing the quality of experience goods (Li and Hitt 2008). As customers are at risk of spending resources on inadequate goods, they often consult other customers' opinions to avoid making inadequate purchases (Senecal and Nantel 2004). Moreover, consumers are most likely to systematically process eWOM when they already have buying intentions (Pan and Zhang 2011). However, effects of customer ratings on perceived product quality and choice have been controversially discussed in the literature. Chevalier and Goolsbee (2003a; 2003b), Chevalier and Mayzlin (2006) or Li and Hitt (2008) argue that Amazon's product ratings given by other customers significantly affect purchase decisions. Yet some studies report that consumers perceive negative information as more reliable and persuasive than positive information of a similar intensity ("negativity bias"). Others propose the opposite

(“positivity bias”). Hu et al. (2007) explain this inconsistency by observing that average ratings are skewed: Due to an “underreporting bias” ratings are not normally distributed, but j-shaped. As review posting requires emotional involvement of the customer, and involvement is higher when a good is either really appreciated or really disliked, medium ratings are underrepresented. In addition, many products receive highly positive reviews due to a “purchasing bias” – having assessed a product as sufficiently attractive to spend resources on it, consumers tend to uphold their positive attitude when giving ratings. Thus, other consumers may assign the highest credibility to the (rarely occurring) negative ratings and refrain from buying low-rated goods.

*Hypothesis 2a. A high fraction of positive ratings positively influences the good’s sales.*

*Hypothesis 2b. A high fraction of negative ratings negatively influences the good’s sales.*

In contrast, Chen et al. (2004) and Liu (2006) establish a positive influence of the number of reviews posted rather than the direction of the ratings. As reviews are subjective, the assessment of their appropriateness and validity is difficult. Consequently, consumers might rather rely on the total number of review posts, as an indicator for popularity and relevance, than on the content of individual reviews. The effect of relatively many reviews may be more pronounced for niche goods, as in the long tail other sources of product information (e.g., by the retailer, the media, or advertising) are comparably sparse. So far, effects of the number of WOM comments, “WOM volume”, remains underresearched – perhaps as WOM traditionally reached only few direct contacts. Yet today, online communities enable consumers to spread eWOM almost unrestrictedly, and eWOM may be stored and accessed for long periods of time. However, one might assume that the marginal impact of additional reviews decreases as the overall number of reviews becomes high. After a threshold, readers may even be less interested in buying a good that has an immense number of reviews already as such goods may appear to become an “old hat”. Consequently, we expect the relationship between the number of reviews and a good’s sales to be inversely u-shaped.

*Hypothesis 3a. A high number of customer reviews positively influence the good’s sales.*

*Hypothesis 3b. There is an inversely u-shaped relationship between the number of customer reviews and a good’s sales.*

Top-rated reviewers who have a long and documented history of reviewing may appear most trustworthy sources of advice to consumers. Besides, as consumers are constantly at risk of buying the “wrong” goods, particularly with niche goods, they may prefer products included in a top-reviewer’s potentially more knowledgeable “pre-selection”, i.e. prefer buying goods which top reviewers have found worth buying, too.

*Hypothesis 4. Being reviewed by a top reviewer positively influences the good’s sales.*

Similarly, consumers may choose books for which the level of discussion among consumers is high, indicating that many others have considered a particular book worth reading as well. The literature also argues that for fiction books, decision criteria largely follow Adler’s (1985) principle of “the more you know, the more you enjoy”. That is, people intentionally hear the same music, watch the same movies and read the same magazines and books (Elberse and Oberholzer-Gee 2006). Thereby, they accumulate knowledge they can use for subsequent discussion of these goods with other consumers for social entertainment. In choosing the *most popular* goods, consumers minimize their search costs for finding discussion partners. Therefore, consumers may prefer buying goods with larger ‘user communities’ because it becomes easier to find interaction partners.

*Hypothesis 5. WOM in consumer forums positively influences the good’s sales.*

Another strategy to reduce customer uncertainty when buying experience goods is to offer a free trial. Online book retailers can provide reading excerpts which help assess book quality. The situation is similar to a movie producer who uses a trailer to provide consumers with information on the central elements of the film, thereby offering an incentive to “come back for more”. Amazon.de started providing excerpts (“Search Inside!”) in 2005.

*Hypothesis 6. Offering free online trial positively influences a good’s sales.*

Evoking vividness can be done by providing product pictures (Weathers et al. 2007). Here, a book’s cover is analogous to a product’s package; it delivers direct (title, drawings, pictures) as well as indirect (colors,

material) information about the book. Sometimes covers directly reflect book content (e.g., people interlacing for a romance novel), at other times, they may be more or less relevant allusions (e.g., a dollar sign on the cover of a stock market book). Several studies argue that covers affect consumers' product evaluations. Then, offering a cover as a "vivid" component should have a positive impact on readers' perceived ability to form some impression about product quality.

*Hypothesis 7. Offering vivid information positively influences a good's sales.*

Long tail theory predicts that consumers will become particularly attracted to buying niche products as those match personal preferences better than mainstream products (Anderson 2006; Brynjolfsson et al. 2003; Chevalier and Goolsbee 2003a). The rationale is based on the notion that goods are heterogeneous in search costs – there is high customer awareness for hits as numerous information sources are readily available (advertising, on-site promotions, newspaper reports, bestseller lists, etc.). Then, information offered by e-retailers communication practices in terms of product networks, user-generated content (reviews, discussions), free trial and vivid cues should play a more important role for generating sales in the long tail where search costs are high, than in the hit segment of the distribution. In effect, long tail theory argues that reducing search costs for consumers fosters a shift in the sales distribution, away from hit products to the niche. Thus, the sales distribution may gradually move towards greater equality compared with previous conventional distributions.

*Hypothesis 8. Product networks, user-generated content, free trial and vivid information have a greater impact on sales in the tail of the sales distribution than in the head.*

*Hypothesis 9. Product networks, user-generated content, free trial and vivid information gradually alter the sales distribution towards equality.*

## Data

Our data is mainly collected from the German website of Amazon, [www.Amazon.de](http://www.Amazon.de). In Germany, Amazon has been the largest book retailer in terms of sales compared with [bol.de](http://bol.de), [buch.de](http://buch.de) or [buecher.de](http://buecher.de). To generate the sample, we follow a procedure in line with previous literature (Chevalier and Mayzlin 2006). Using Perl-based scripts, we collect data on 60,000 books from the Amazon.de website. We used Amazon's bestseller lists (each book category has its own list) as a starting point and collected 9,600 titles from these lists in all the 22 main book categories. We added a random sample of 10,000 books from the official German "Books in Print" directory ([www.vlb.de](http://www.vlb.de)). As usually, a large fraction of sales are concentrated on a small fraction of books, the procedure ensured the inclusion of niche titles in the sample. Then, we added all those books that were automatically recommended by the product network for all the 19,600 books, yielding the overall sample size (60,000 books). We considered only German-language books from Amazon.de. We collected data on ISBN (serial number), author, publisher, price, page count, format, release date, stock, availability of reading excerpt and cover, recommendations, number of reviews and distribution of reviews across the five-point scale, top-reviewer activity and discussion forums for each of the books in our sample. Following previous studies on the German book market, we used [bol.de](http://bol.de), [buch.de](http://buch.de), [buchreport.de](http://buchreport.de), [vlb.de](http://vlb.de), and authors' homepages if information on a book was incomplete. Finally, we collected the Amazon sales rank of each book. Amazon.de explains that for books in the top 10,000 ranks, the rankings are updated hourly based on the sales activity of the last 24 hours; for books ranked 10,001-100,000, ranks are updated once per day; for books ranked higher than 100,000, ranks are updated once a month. According to Amazon.de, books that were not purchased at least once in the past month are not ranked (Chevalier and Goolsbee 2003a; Chevalier and Mayzlin 2006). We collected sales rank data for each of our books twice a week in a four-week period and computed an average rank for each title based on these eight observations, which, according to the literature, should allow an adequate approximation of "true" sales ranks (Chevalier and Mayzlin 2006; Rosenthal 2008). We excluded all those books which failed to provide eight rank observations in the data collection period. The final sample comprises 33,609 books.

Prior literature on demand for books used sales rankings as an adequate proxy when actual sales data was unavailable (Brynjolfsson et al. 2003; Chevalier and Goolsbee 2003a; Rosenthal 2008; Schnapp and Allwine 2001). Some studies used rankings from bestseller lists instead; however, this approach might lead to biased results because these studies focus only on successful books. Brynjolfsson et al. (2003) and Chevalier and Goolsbee (2003a) established that the relationship between sales ranks and sales at

Amazon.com is approximately log-linear:  $\ln[\text{sales}_i] = \beta_0 + \beta_1 \ln[\text{rank}_i]$ . Schnapp and Allwine (2001) used proprietary data from a single publisher and related that publisher's online sales at Amazon.com in May 2001 to sales ranks for a subsample of titles. They found the following linkage:  $\ln[\text{sales}_i] = 9.61 - 0.78 \ln[\text{rank}_i]$ . Chevalier and Mayzlin (2006) continued using these estimates, scaled up by 24% (the growth in Amazon.com's North American sales for the period that had passed since Schnapp and Allwine's (2001) data collection). Using the same log-linear conversion approach and proprietary sales data from a publisher, Brynjolfsson et al. (2003) estimate the relationship between sales and sales ranks for Amazon.com as  $\beta_0 = 10.526$  and  $\beta_1 = -0.871$ . Although Germany is one of the largest book markets in the world, the U.S.-based estimates would overestimate German sales: The U.S. market considerably exceeds the German one (total sales in 2007: €9.5 billion in Germany, €5.2 billion in China, €17.6 billion in the U.S.; Buchreport 2009). Therefore, we estimated a conversion model for the German market. Based on the literature, we proceeded as follows: Amazon.de provides information on stock shortage if books have five copies left or less. This information is updated several times a day. Based on our initial sample of 60,000 books, we extracted all the books for which a shortage notice was displayed at Amazon.de (14,000 titles). Then, we documented stock variations (6,000 cases) and corresponding sales rank variations five times a day for a seven-day period. We excluded all titles which had positive variations in stock and decreasing ranks and all those which had less than one copy left at the end of day seven to ensure that the variation in sales ranks was related to variations in stock (Amazon.de does not stop selling products which are out of stock). We also excluded all titles with increasing ranks (i.e. no sale) and positive variations in stock (i.e. replenishment). Our final sample for estimating the conversion function contained 540 books. Based on this sample, we estimated  $\beta_0 = 8.114$  and  $\beta_1 = -0.656$  for the German market. The model was highly significant ( $p < 0.001$ ). Anecdotal evidence suggests that the estimates are close to "real" figures: For the book "Wetlands" (the No.1 seller in the sample), Welt-Online (2008) reported 3,100 units sold per week by Amazon.de in our data collection period; our model predicts 3,341 sold copies.

Product network recommendations are measured as the sales of all other books that recommend a book at Amazon.de. Fraction of ratings and number of reviews are intuitive; a dummy indicates whether a book was reviewed by a top reviewer (1 – yes, 0 – no). We also measure the number of discussion forums for a particular book at Amazon.de. The provision of free trial (excerpt) and vivid content (cover image) are measured as binary variables as well. We control for book price, for ship time, as e.g., goods that are out of stock or have long ship times may be unattractive to buy, for release dates, and for external sources of "visibility" (dummy indicating whether a book appeared in one of the three leading German literature TV-shows in the month before data collection, and another dummy indicating whether an author received a significant literary prize in the last three years ("Noble Prize in Literature", "Pulitzer Prize", "Peace Prize of the German Book Trade", "Georg Büchner Prize", "Ingeborg Bachmann Prize")). We control for whether a book was published by one of the 50 biggest publishing houses (dummy variable, 1 – publisher belongs to one of the Top50 publishing houses according to the "Top100 publishers" study by Buchreport (2008), 0 – otherwise).

## Methods and Model Specifications

We use both ordinary least squares (OLS) regressions (controlling for absence of multicollinearity, heteroscedasticity, and the distribution of disturbance terms) and quantile regressions (QR). QR estimates a conditional mean function that describes how the mean of  $Y$  changes with a covariate  $X$ , assuming that  $X$  affects only the location of a conditional distribution, not the scale or other aspects of its distributional shape (Koenker and Hallock 2001). Yet, we expect communication practices to vary in impact on books across the sales distribution and, consequently, OLS estimates are not necessarily reliable to specify the strength or even the direction of effects on the lower vs. the upper end of the distribution. Previous literature has used conditional quantile regression models to measure the impact of explanatory variables on distributional statistics that go beyond the mean. QR estimates a specified conditional quantile of the response variable as a linear function of the covariates, and permits a more complete description of the conditional distribution than conditional mean analysis alone. QR allows describing how the median, or perhaps the 10th or 95th percentile of the response variable, are affected by a regressor (Koenker and Hallock 2001). Consequently, this method intends to shed light on how the entire distribution changes with certain independent variables (e.g. Koenker and Hallock 2001). As the QR approach does not require strong distributional assumptions, it offers a distributionally robust method of modeling these relationships (Koenker and Machado 1999).

However, a useful feature of OLS regressions is that they provide consistent estimates of the impact of an explanatory variable,  $X$ , on the population *unconditional* mean. Hence, estimates can be used to measure the impact on the mean of  $Y$  of e.g. increasing every observation's  $X$  value by one unit, holding everything else constant. On the contrary, estimates obtained from conditional quantile regressions cannot be used to estimate the impact of  $X$  on the unconditional distribution, as conditional quantiles do not average up to their unconditional population counterparts (see also, Firpo et al. 2009). Accordingly, Firpo et al. (2009) propose a new regression method called *unconditional quantile regression* (UQR). That is, UQR allows measuring the effect of a small change in independent variables on any functional of the unconditional sales distribution, in a similar sense as the coefficients of an OLS model capture marginal effects on the mean in standard regressions. Focusing on the unconditional instead of the conditional distribution allows answering questions such as “What are the distributional effects on sales of adding one review to each book?” or “What is the effect of increasing the proportion of books with reading excerpts?” Therefore, UQR runs OLS regressions of a transformation – the re-centered influence function (RIF) – of the sales variable on the explanatory variables. The RIF for the quantile of interest  $q_\tau$  is defined as  $RIF(Y; q_\tau) = q_\tau + ((\tau - I(Y \leq q_\tau))/f_Y(q_\tau))$ , with  $q_\tau = Q_\tau(Y)$  being the  $\tau$ th population quantile of the unconditional distribution of  $Y$ ,  $f_Y$  is the marginal density function of  $Y$  and  $I$  is an indicator function. The RIF is simply a dichotomous variable that takes the value  $q_\tau - (1 - \tau)/f_Y(q_\tau)$  when  $y$  is below the quantile  $q_\tau$ , and  $q_\tau + \tau/f_Y(q_\tau)$  when  $y$  is above the quantile  $q_\tau$ .  $RIF(Y; q_\tau)$  is unobserved, but the sample analog is  $RIF(Y; q_\tau^\wedge) = q_\tau^\wedge + ((\tau - I(Y \leq q_\tau^\wedge))/f_Y^\wedge(q_\tau^\wedge))$ , where  $q_\tau^\wedge$  is the  $\tau$ th sample quantile and  $f_Y^\wedge$  is the kernel density estimator. For sensitivity analyses, we apply Huber Sandwich calculations, valid under independent but non-identical sampling, and obtain the individual scalar sparsity estimates using kernel residuals. We also use bootstrap resampling to calculate the covariance matrix. Huber Sandwich and bootstrap techniques produce concurring results, indicating result reliability. If e.g. recommendation systems were in fact more beneficial for niche products sales – as the long tail view suggests – we should observe an increase in the respective coefficients for some quantiles  $\tau$  in the lower tail of the unconditional sales distribution. Then, recommendations, reviews, discussions etc. would have a higher impact on niche products.

## Results

Table 1 displays the results of the OLS regression. Table 2 presents correlations. Most of our hypotheses are supported. The model explains 54 percent of the variation in book sales. The results indicate that the product network (H1), user-generated content in terms of reviews (H2, H3), top reviewer involvement (H4) and discussions (H5), free trial (H6) and vivid information in term of provision of a book cover (H7), have significant effects on demand. Whereas the influence of most variables is positive and significant, the fraction of 1-star ratings negatively affects book sales, as hypothesized (H2a, H2b), and positive effects of WOM volume in terms of the number of reviews holds only up to a threshold, after which the effect of WOM volume on sales turns negative (H3a, H3b). According to the standardized coefficients, the strongest influence on purchase decisions can be attributed to providing free trial. Yet interestingly, apart from free trial, consumer demand is particularly dependent on negative assessments by other consumers (fraction of 1-star ratings), revealing that the negativity bias is of fundamental importance for purchase decisions. Apart from negative opinions, product recommendations also have a strong impact on sales, followed by providing vivid information. All coefficients are highly significant, which is obviously promoted by large sample size. However, repeatedly drawing random samples and re-running regressions does not structurally alter our results.

The controls show that high price, ship time and time since release have significant negative impacts on sales, whereas external marketing effects in terms of TV appearance, being published by a well-known publisher and receiving a literature award enhance sales.

Table 3 displays the unconditional quantile regressions results. *Product recommendations* strongly enhance sales for goods in the long tail (H8), but also, in the upper quantiles of the distribution, and even for the hits. Consequently, this result supports long tail theory only to some extent, as long tail theory implies that an increase in retailers' use of recommendations is particularly beneficial for niche products.

Concerning the influence of user-generated content in the various parts of the sales distribution, we obtain mixed results. A high *fraction of 5-star ratings* is influential in the lowest quantile of the sales distribution, and the positive impact of 5-star ratings decreases from the lowest quantile towards the middle of the sales distribution; this development is reversed from the 40<sup>th</sup> quantile on, when the positive



impact of 5-star reviews increases. From the 80<sup>th</sup> to 90<sup>th</sup> quantile the coefficient drops to its lowest value, indicating that for top-sellers, positive reviews matter the least. In contrast, as the coefficient of *1-star ratings* indicates, negative reviews lose their overall destructive impact in the long tail. Interestingly, in the lowest quantiles, the coefficient changes its sign, indicating that even a highly critical review is better than none at all for driving niche product sales. In the mid and top quantiles, negative reviews significantly decrease sales, as expected. *WOM volume* (the number of reviews) affects sales increasingly positively along the distribution from the slow-sellers up to the hits, and the effect of WOM volume on sales is u-shaped (but the coefficient for the squared term is small). That is, in contrast to H8, which postulates a low impact of WOM volume for the hits, we find steadily increasing coefficients. *Top reviewers' opinions* enhance sales along the distribution as well, although their impact decreases for goods that are selling very well already (Q90). The effect of *discussion posts* is insignificant for low-selling works, but steeply increases from the middle of the distribution to top-selling works, which is again counter to H8. In line with long tail theory, *free trial* enhances sales particularly for niche products (H8). Its impact is of mixed importance across the quantiles; it decreases from the low quantiles to the mid quantiles, and becomes altogether insignificant for goods that sell well already (Q90). As regards *vivid content*, providing a cover image does not affect sales in the middle quantiles. However, vivid content enhances sales in the lower quantiles, as well as in the upper and top.

The controls show that price affects sales negatively along the entire distribution, if slightly more so for low-selling than top-selling goods. Higher ship time is disadvantageous for products that do not make it to the highest quantiles. Sales decline with time across the distribution. External marketing effects arising from TV appearance decrease sales in the long tail and up to the upper middle of the sales distribution, but strongly enhance demand for well-selling works. A top publisher is increasingly beneficial for sales along the distribution from niche to hits. Effects of winning a literature prize are somewhat mixed, the strongest positive effect occurs for books behind the best-selling works, lying in wait to move up the distribution to the top quantiles.

Resulting from the varying effectiveness of communication practices for enhancing sales across the distribution, there are some initial implications concerning H9: Contrary to long tail theory's expectations, a "flattening" of the sales curve (H9) may not necessarily occur. Instead, as retailers increasingly use recommendation systems, sales gains for low-selling goods may rather come at the expense of sales for those goods currently positioned in the mid quantiles, where the influence of recommendations is the lowest. For user-generated content, implications are mixed; enhancing some kinds of WOM may drive sales towards the niche (extreme ratings; in particular, the fraction of 1-star ratings), others may rather move sales towards the upper quantiles (fraction of 5-star ratings, top reviewers' opinions) or even, to the top (WOM volume, discussions). Increasing free trials, in contrast, may support the long tail argument. Yet, similar to the impact of recommendations, increasing vivid content may enhance sales both in the niche and for the hits, but could shift sales away from works in the mid quantiles. These effects could be explored in much more detail using longitudinal datasets.

As regards additional analysis, we also controlled for book length and book format (paperback dummy), with insignificant results. Correlations hint that there is a preference for paperbacks, yet overall results are inconclusive. In addition, we split the sample into subgroups according to book genres. As book categories at Amazon are non-exclusive (i.e., books can be listed in quite different categories), we apply additional category-based analysis to the more general distinction of fiction vs. nonfiction books. Splitting up the sample and rerunning OLS and UQR regressions does not significantly alter the results; yet, for books with a technical content, effects of social influence are even more decisive. Here, decisions are based on WOM, i.e. ratings and discussion entries, even more strongly than for fiction books (according to the respective standardized coefficients). The impact of social features on purchase decisions for technical books seems particularly interesting: Although buying what others bought does not make the acquired knowledge at all exclusive, consumers seem to believe that the 'wisdom of crowds' at least insures against making bad choices. We find weaker support for effects of providing vivid content for technical books; coefficients are slightly outside the 10 percent range in most quantiles. Possibly, the design of nonfiction books does not vary much compared with other genres – e.g. for business books, often, covers display financial symbols, business people, or mathematical formulas. However, for fiction and nonfiction books alike, readers' interest is greater when recommendations are many and when there is free trial provided.

We have further established that the directions and significance levels of the variables all remain stable under various different specifications of the models. Our results are robust.

<b>Method: OLS</b>	<b>Model 0 Coefficient</b>	<b>Model 1 Coefficient</b>	<b>Model 1 Standard Error</b>	<b>Model 1 Standardized Coefficient</b>
Product network recommendations		0.376***	(0.004)	0.225
Fraction of 5-star ratings		0.416***	(0.009)	0.037
Fraction of 1-star ratings		-0.226***	(0.026)	-0.419
Number of reviews		0.010***	(0.001)	0.040
Number of reviews <sup>2</sup>		-0.001***	(0.000)	-0.068
Top reviewer opinion		0.130***	(0.011)	0.072
Discussions		0.490***	(0.051)	0.042
Reading excerpt		0.088***	(0.011)	0.438
Cover		0.052***	(0.010)	0.114
Price	-0.007***	-0.006***	(0.001)	-0.087
Ship time	-0.047***	-0.044***	(0.003)	-0.032
Weeks since release	-0.000***	-0.000***	(0.000)	-0.027
TV appearance	1.930***	1.873***	(0.251)	0.030
Top50 publisher	0.084***	0.076***	(0.008)	0.045
Literary prize	0.442*	0.426*	(0.170)	0.013
<i>Constant</i>	0.345***	0.307***	(0.020)	0.225
N	33,609	33,609		
F	923.32***	1634.22***		
R <sup>2</sup>	0.09	0.54		

Dependent variable ln[sales]. Significance levels (2-tailed): \*\*\*p<0.001; \*\*p < 0.01; \*p < 0.05; †p < 0.1.

**Table 1: OLS Results**

Variable	Mean	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(0) Sales ranks	108,270.500														
(1) Product network recommendations	19.279	-0.35***													
(2) Fraction of 5-star ratings	0.446	-0.24***	0.21*												
(3) Fraction of 1-star ratings	0.039	0.43***	0.09	0.34***											
(4) Number of reviews	6.895	-0.27***	0.34***	0.22***	-0.10*										
(5) Top reviewer opinion	0.195	-0.26***	0.28**	0.14*	0.03	0.32***									
(6) Discussions	0.013	-0.22***	0.33***	0.03	0.09	0.36***	0.17*								
(7) Reading excerpt	0.158	-0.49***	0.20**	0.20***	0.05	0.35***	0.19***	0.23***							
(8) Cover	0.663	-0.43***	0.21**	0.12*	-0.13**	0.27***	0.22***	0.17**	0.43***						
(9) Price	15.787	0.14**	0.13**	0.13	-0.17**	0.16*	0.12†	0.26*	0.15**	0.16***					
(10) Ship time	0.422	0.23**	0.05	0.09	0.03	0.04	-0.00	0.02	0.08	0.01	0.07				
(11) Weeks since release	188.452	0.22***	0.09	0.05	0.06	0.43***	0.07	0.08	0.02	0.04	-0.23***	0.16*			
(12) TV appearance	0.000	-0.28**	0.14***	0.11*	0.12*	0.12†	0.18***	0.10†	-0.13**	0.10	0.15*	0.04	-0.19***		
(13) Top50 publisher	0.285	-0.21***	0.17†	0.18**	-0.07**	0.07	0.04	0.07	0.14**	0.30**	0.13	0.21*	0.06	0.25***	
(14) Literary prize	0.001	-0.18*	0.02	-0.16***	0.03*	0.09*	0.10**	0.12†	0.08	0.02	-0.08	0.03	-0.01	0.04	0.23**

Correlation table based on the conversion model sample. Significance levels (two-tailed): \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05; † p < 0.1.

**Table 2: Correlations**

Method: RIF-Regression	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Product network recommendations	0.478*** (0.003)	0.357*** (0.003)	0.195*** (0.003)	0.235*** (0.003)	0.287*** (0.003)	0.371*** (0.004)	0.491*** (0.005)	0.652*** (0.008)	0.708*** (0.014)
Fraction of 5-star ratings	0.406*** (0.013)	0.375*** (0.010)	0.373*** (0.010)	0.397*** (0.010)	0.421*** (0.011)	0.466*** (0.013)	0.509*** (0.017)	0.514*** (0.022)	0.357*** (0.028)
Fraction of 1-star ratings	0.155** (0.048)	0.020† (0.037)	-0.043 (0.034)	-0.109** (0.033)	-0.157*** (0.034)	-0.222*** (0.038)	-0.320*** (0.046)	-0.535*** (0.060)	-0.677*** (0.076)
Number of reviews	0.000*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.006*** (0.000)	0.009*** (0.001)	0.016*** (0.001)	0.027*** (0.002)
Number of reviews <sup>2</sup>	-0.000* (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Top reviewer opinion	0.085*** (0.009)	0.100*** (0.009)	0.113*** (0.009)	0.125*** (0.010)	0.142*** (0.012)	0.174*** (0.015)	0.182*** (0.019)	0.233*** (0.028)	0.184*** (0.040)
Discussions	-0.037 (0.024)	0.008 (0.022)	0.056* (0.025)	0.104** (0.030)	0.132*** (0.037)	0.224*** (0.050)	0.373*** (0.072)	0.724*** (0.113)	1.420*** (0.189)
Reading excerpt	0.112*** (0.014)	0.087*** (0.011)	0.082*** (0.011)	0.082*** (0.012)	0.077*** (0.013)	0.084*** (0.015)	0.069*** (0.019)	0.078** (0.026)	0.053 (0.035)
Cover	0.040** (0.013)	0.021* (0.010)	0.017† (0.010)	0.005 (0.010)	0.012 (0.011)	0.024† (0.012)	0.027† (0.015)	0.061** (0.021)	0.127*** (0.028)
Price	-0.009*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)
Ship time	-0.101*** (0.006)	-0.057*** (0.004)	-0.040*** (0.003)	-0.031*** (0.003)	-0.027*** (0.003)	-0.022*** (0.003)	-0.017*** (0.004)	-0.016** (0.005)	0.004 (0.006)
Weeks since release	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
TV appearance	-0.513*** (0.062)	-0.476*** (0.061)	-0.501*** (0.073)	-0.517*** (0.090)	-0.508*** (0.115)	-0.474** (0.156)	-0.176 (0.218)	0.793* (0.315)	4.222*** (0.422)
Top50 publisher	0.020† (0.011)	0.042*** (0.008)	0.066*** (0.008)	0.072*** (0.009)	0.081*** (0.010)	0.095*** (0.012)	0.108*** (0.015)	0.138*** (0.021)	0.128*** (0.029)
Literary prize	0.039 (0.082)	0.114 (0.085)	0.196* (0.098)	0.121 (0.119)	0.291* (0.137)	0.308† (0.179)	0.606* (0.266)	1.637*** (0.425)	0.681 (0.869)
Constant	-0.201*** (0.028)	-0.040† (0.021)	0.070*** (0.020)	0.146*** (0.019)	0.225*** (0.020)	0.268*** (0.022)	0.312*** (0.025)	0.417*** (0.031)	1.043*** (0.038)
Pseudo R <sup>2</sup>	0.16	0.20	0.24	0.28	0.31	0.33	0.34	0.32	0.26
Dependent variable ln(sales). Significance levels (2-tailed): ***p<0.001; **p < 0.01; *p < 0.05; †p < 0.1. Robust standard errors in parentheses.									

**Table 3: Unconditional Quantile Regressions Results**

## Discussion

Consumers face quality uncertainty when shopping experience goods (Stiglitz 2000). Consequently, they will search for information to reduce the risk of making inadequate purchases (Hirshleifer 1965). Based on a first long tail conversion model for a sizeable non-U.S. market, we study the relative effects of four increasingly applied communication practices on driving purchase decisions overall and in the sales distribution's different segments, using the context of online book retail. These practices – provision of product recommendations, user-generated content, free trial and vivid content – have not been studied together before and include demand drivers that have been often overlooked (e.g. discussion forums and free trial). In particular, little is known about the effects of such communication practices on sales prospects in the various segments of the sales distribution.

Our results indicate that recommendation systems, eWOM in terms of extreme ratings, free trial, and vivid content are key to driving sales in the long tail. Effects of ratings on niche sales are striking: Positive reviews enhance sales for low-selling works – yet contrary to expectations, negative ones enhance sales as well. In the niche, where goods are mostly found via specific queries for refined interests, critical reviews lose their bite (“all publicity is good publicity”), while positive ones obviously confirm the supposed attractiveness of a good for consumers. In the front end of the sales distribution (for hit products), recommendations, popularity indicators like WOM volume and discussion posts, and image provision are highly influential buying arguments. The impacts of these variables increase in strength in the high quantiles. This result is even more relevant in light of the findings by Elberse and Oberholzer-Gee (2006), who established that the number of titles in the top 10 percent of VHS and DVD weekly sales had dropped by over 50 percent between 2000 and 2005. Given that sales become concentrated on fewer best-selling titles (Elberse 2008) retailers may reinforce this effect by increasing WOM volume and discussions. In the highest quantiles, the impact of popularity indicators like WOM volume and discussions may even outshine the importance attached to other kinds of user-generated content like positive ratings and top-reviewers' opinions. Popularity also seems to reduce the effectiveness of free trial, although free trial allows evaluating purchase options without having to rely on third-party opinions. Besides, advertising campaigns and offline promotion (TV appearances, literature prizes) are beneficial as additional sources that inform consumers about product popularity. In sum, a simple recommendation based on our findings would be that online retailers closely monitor their goods' individual positions, and changes thereof, within the sales distribution of their entire offering. Simultaneously, focusing on communication practices-segment fit is essential: Retailers need to structure and adapt their communication practices to the different segments of the sales distribution, as the empirical evidence establishes that the effectiveness of these practices largely differs across bestsellers and slow sellers as well as other segments.

As regards practical implications for focusing efforts, our results can help retailers select, combine and focus communication practices, and show how to adapt such practices to the various parts of the sales distribution. For example, eWOM has been claimed to be a valuable venue to influence consumer product evaluations. However, WOM is not universally beneficial. Some studies found that WOM dispersion or valence (Chevalier and Mayzlin 2006) have significant effects on sales, while others found WOM volume to be the sales driver (Chen et al. 2004; Liu 2006). Our results provide conclusive insights into where WOM is, and what kinds of WOM are, most useful to enhance sales. If focusing on niche products, *extreme* reviews increase sales. However, the reviewing system needs intervention for maximum effect: During 2007–2010, Amazon.com went through several changes in how to present user-generated reviews to consumers; the firm initially presented reviews according to their recency, then valence, then their importance from the firm's perspective (“spotlight reviews”), and recently, consumer-rated helpfulness (Pan and Zhang 2011). Yet according to our results, presenting extreme reviews first and leaving medium ratings for later might work best in the niche.

On the downside, user-generated content represents an information source that competes with retailer-provided content, reducing the retailers' ability to influence consumers via traditional marketing and advertising channels. Yet on the upside, reviews are comparatively cost-efficient, as user-generated community content requires lower input and maintenance than retailer-provided content. Whereas the presentation of recommendations, free trial and vivid content are controlled by the retailer, supporting users in generating eWOM that is not only informative, but also benefits products sales in the different segments, needs to be encouraged and incentivized. Incentivizing can turn out difficult as reviewers may have very different motivations to spread eWOM (e.g., venting negative feelings, providing social benefits,

gaining publicity). Accordingly, mechanisms that incentivize WOM will need experimenting and fine-tuning over time. Such mechanisms could include, for example, in the niche offering chances of winning coupons for other books or products for extreme, “outspoken” ratings (benefitting the long tail); while in the upper segments, increasing WOM volume (up to a threshold, benefitting the hits most) might be promoted e.g. through granting user-voted “most helpful reviewer of the month” labels, so that reviewers interested in popular goods may gain some personal popularity.

Moreover, on the premise that reducing search costs leads to intensified consumer search, retailers often fear increased competition. Our results provide insights into integrating assortment and promotional strategies in a way that takes advantage of changes in consumer search behavior. Long tail theory holds that increasing the use of communication practices that reduce consumers’ search costs and purchase uncertainty could support a paradigm change in retailing – away from the 80/20 distributed sales of a Pareto world to a more even sales distribution of a long tail world. However, exploring implications of our results, a development in favor of niche products may not necessarily imply a “flattening” of the sales curve, as predicted by long tail theory. Rather, increasing the use of some communication practices, like recommendations and vivid content, could drive away sales particularly from books currently reaching a medium sales position, so that the niche, the upper segments, and the hits would benefit. On the premise that the entire market size is relatively stable, an increase in the use of other practices that particularly benefit either the niche, or the hits, but not predominantly the medium quantiles (e.g. extreme reviews, WOM volume, discussion posts), would be additionally disadvantageous for current medium sellers. In consequence, both the predictions made by long tail and superstar theories would have some merit, and the two theoretical bases would need more extensive integration and reconciliation in future research.

Regarding assortment strategies, one question remains: Will enhanced communication practices in online retailing change the economics of experience good markets so that retailers should refocus assortment and promotional strategies on the long tail? On the supply side, online markets feature nearly unlimited shelf space, so the opportunity costs of listing niche products converge to zero (Brynjolfsson et al. 2003). E-retailing also allows aggregating geographically dispersed demand, which increases the sales volume of slow sellers compared with sales attempts through conventional channels. However, our results on effects of communication practices in the upper segments indicate a likelihood that ultimately, popular goods remain in the focus of consumer interest and a paradigm change, customers turning away from mainstream products towards niche products, will not occur. Rather, consumers will be attracted to firms that offer a large selection of niche (and popular) products, and provide adequate IT-enabled surfaces that help discover and evaluate these goods. Then, niche products are an additional revenue source that allows retailers gain an advantage over their brick-and-mortar counterparts (Brynjolfsson et al. 2010) as well as over other e-retailers using less refined communication practices.

Thereby, consumers’ online information search creates economic opportunities for numerous actors, foremost, producers and retail organizations. At the same time, consumers’ purchase decisions, being informed by current communication practices, in turn have an effect on the information content that subsequent communication will transport – either by actively participating in social exchange, when consumers offer their opinions on recent purchases in review posts and forums; or simply, by passively affecting the linkages in the product network, as consumers’ recorded buying choices contribute to the layout of future recommendation links.

Regarding limitations, we do not study effects of online retailers developing abilities to provide personalized information (Weathers 2007; Wind and Rangaswamy 2001), as the product, not the consumer is the main data source. Moreover, future longitudinal studies could provide valuable dynamic insights in sales curve developments over time. Future research could also assess how communication practices and assortment strategies together drive consumers’ choices of which e-retailer to buy from, and how e-retailers can counter price-competition risks resulting from low search and switching costs in online channels by differentiating via the “right” combination of assortments and communication strategies.

## **Conclusion**

The availability of electronic data containing information about social exchange among people and linkages between products provides researchers with an unprecedented microscopic view of the interdependencies of commercial and social features (Oestreicher-Singer and Sundararajan 2012).

Studying the effects of four distinct online communication practices that are increasingly used by e-tailers, first, we demonstrate that these practices vary greatly in their effectiveness for influencing consumers' purchase decisions. Second, we provide insights into probable shifts in the sales curve in response to the selective use of these communication practices (i.e., whether a redistribution of sales between bestsellers and niche products takes place). Our results reveal that both bestsellers and niche products gain sales at the expense of medium-popular products. Therefore, our findings run counter to theoretical predictions and the few previous studies in the field. Rather than a "lowering of the head" and "elongation and fattening of the long tail" (Anderson 2006) of the sales curve or a "rising of the head" and "flattening of the tail" (Elberse 2008), selective use of the four practices can raise both the head and tail but flatten the middle of the sales curve. Thereby, the results enhance our understanding of the effectiveness of online communication tools.

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